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IoT-Enabled Forecasting of Vehicle Based Carbon Emissions and Smart Fuel Management: Optimizing Efficiency and Performance

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Abstract: The implementation of an IoT-based device in the vehicle for capturing, notifying, monitoring and analyzing the real time data of the vehicles through gas, dust density sensors and notifications through mobile application. Sensor generated data transfer to electronic sensor data processing microcontroller ESP-32 into human readable values through cloud on Mobile application or Web Based application. Captured data through sensors successfully demonstrates the objective based methodology and framework to measure the individual vehicle carbon emission. Notification displays on Mobile application through IoT device sensors to monitor and manage fuel consumption effectively, predicting usage patterns, optimizing routes, and suggesting fuel-saving measures based on real-time data analysis

Keywords*: Environmental Protection Agency, Air Quality Index, Clean Air Act, Internet of Things (IoT), Carbon Monoxide, Carbon Di Oxide, Particulate Matter, Graphics Processing Unit*

1. Introduction

Nowadays pollution is a major concern in front of the world. The EPA decided certain levels of an AQI for the pollutants in the air. As per CAA these pollutants have an air quality standard that becomes national standard of the EPA. So, it will help to protect the health of living being.

- Carbon Monoxide
- Ozone
- Air Particles
- Sulfur Dioxide
- Nitrogen Dioxide

Out of these five gases, carbon emission occupies most of the part in the atmosphere. It occupies approximately 84% of carbon emissions in the atmosphere. The following chart gives detail information about all pollutants.

Among the various pollutants, carbon dioxide emissions have reached an alarming level. Many countries are dealing with this problem. Transportation is one of the major contributors in producing carbon emissions into the atmosphere. It demanding continuous monitoring to anticipate its impact on air quality. The degradation of air quality indexes leads to many health issues and adverse effects on living

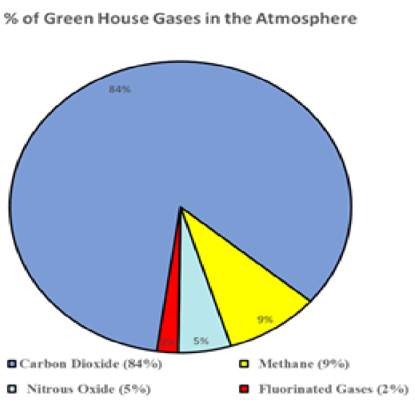

Fig. 1 Greenhouse gases in the atmosphere

beings. With each passing year, the escalation in the number of vehicles directly correlates to the rise in carbon emissions. Urban or metropolitan areas notably exhibit substantially higher vehicular emissions compared to rural regions. Carbon emission stands as a pivotal factor fueling global warming on a global scale. Notably, transit buses, heavy-duty vehicles, and personal transportation means substantially contribute to vehicular carbon emissions through the combustion of fossil fuels.

2. Literature Survey

A considerable amount of research is going on for the prediction of carbon emission in the atmosphere. It harms the environment badly and put adverse effects on human health.

An IOT-based model [1], used different sensors to measure environmental conditions, temperature [17], humidity related data. Based on the user's preferences and the distance between each route, it recommends an alternate route that is free of pollution. The Google map API used in the development of the web application allows for the suggestion of alternate routes and the condition of pollution.

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Vehicle pollution monitoring system based on the Internet of Things (IoT) [2], attached sensors with the Arduino Uno analyzes the level of pollutants from the vehicle exhaust. An alert message is sent to the car owner twice or three times as a warning if the threshold value is exceeded; if the owner declines to fix it, the message is forwarded to the appropriate authorities.

According to the "IOT based Vehicle Pollution Monitoring System" [3],[12], incomplete fuel combustion is the cause of emission level violations. The system in place keeps a constant eye on each vehicle's emission level. A Wi-Fi module, a controller, and gas sensors were used in an IoT kit. This item is installed physically in each vehicle's exhaust system. Data regarding vehicle emissions is connected to gas sensors and sent to a controller, which transmits

In this paper [4], Linkage model used to study the three different kinds of market, trading market for carbon emission, oil market, and the natural gas market. These models implemented to study the mechanisms of these markets for carbon emission by using correlation and clustering mechanisms. It works and predicts emission in a cluster.

This paper [5], analyzing technological and efficiency-based changes by applying a spatial dynamic model to reduce carbon emission effectively. It discusses the development of technology affects carbon emissions. It demonstrates that changes in efficiency have a greater impact than changes in technology. It investigated the various impacts of technological advancement on carbon emissions by combining spatial dynamic econometrics with the SBM-GML technique.

This study [6], inspects aspects that influence the acceptance of a cashless payment system in Malaysia. It adopts the technology of a cashless system to avoid the traffic at petrol pumps. Long queue evading gives so much relief from the traffic. This technology even gives 24-hour access to fuel with no manpower. This study doesn’t include all the aspects of fuel consumption and carbon emission.

The carbon emissions from power generation and direct energy use in an urban area are examined and calculated in this research [7], which was largely disregarded. With the use of the Intergovernmental Panel on Climate Change (IPCC) carbon listing approach, the input-output model for different region measures regional carbon emissions in Beijing.

A comparison of carbon emissions between conservative diesel buses and electric buses has been carried out in this work [8]. According to the study, there were notable differences in the emissions produced by buses operating at different road sites. Energy and diesel buses have variable emission rates and varying sensitivity when it comes to several contributing factors. The GBRT model assesses a high level of carbon emission performance. We only talk about overall estimation here..

The effects of forest fires on biodiversity, greenhouse gas emissions, and flora and fauna are assessed in this research [9]. There are two ecological models that have been used to quantify how forest fires affect net primary productivity. A novel method, similar to delta indices, is suggested for effectively defining burn marks. Using burn indices, it precisely forecasts the effects of jungle fires on greenhouse gas emissions and ecosystem productivity. With the use of remotely sensed data via satellite, the remote sensing technology is utilized to detect terrestrial fires as well as the emission caused by the fire.

By using CALCM and GREET [10], greenhouse gas emissions are calculated for the tesla model. For determining the emission, the life cycle assessment method is used. It shows all the calculated readings of greenhouse gas emissions for the tesla model.

Fuel management system [11], is discussed and developed here, which is efficient, reliable, and helpful as well to reduce the traffic at the fuel station. It stores the all-previous transactions records of fuel refill.

A. Vehicle emission sensors used

Oxygen (O2) Sensors: These are located in the exhaust system and are used to measure the amount of oxygen in exhaust gases. They support the engine control unit's (ECU) efforts to optimize combustion and lower emissions by adjusting the air-fuel mixture.

Carbon Monoxide (CO) Sensors: These devices gauge the amount of the gas present in exhaust emissions. High CO levels indicate incomplete combustion, and CO sensors can assist in identifying combustion inefficiencies.

Nitrogen Oxides (NOx) Sensors: NOx sensors detect and quantify nitrogen oxides in the exhaust gases. They help in controlling emissions by providing feedback to the engine management system for optimizing combustion temperatures and reducing NOx emissions.

Particulate Matter (PM) Sensors: PM sensors detect and quantify the particulate matter present in the exhaust emissions. They are particularly useful for monitoring and controlling fine particle emissions that can have adverse health effects.

Hydrocarbon (HC) Sensors: These sensors measure the concentration of unburned hydrocarbons in the exhaust gases. They assist in identifying issues related to incomplete combustion or fuel system malfunctions.

Exhaust Gas Temperature (EGT) Sensors: These sensors take the exhaust gases' temperature. In order to reduce emissions and enable effective combustion control, they supply data to the engine management system.

Mass Air Flow (MAF) Sensors: While primarily used for measuring incoming air mass for fuel injection control, MAF sensors indirectly influence emissions by optimizing the air-to-fuel ratio.

Exhaust Gas Recirculation (EGR) Sensors: EGR sensors monitor the operation of exhaust gas recirculation systems, which help control NOx emissions by recirculating exhaust gases into the combustion chamber.

Detecting vehicular carbon emissions typically involves using sensors and hardware components capable of measuring various pollutants emitted from vehicles. Some hardware commonly used for vehicular carbon emission detection includes:

Exhaust gas analyzers: These tools detect the amount of contaminants in exhaust gases from moving cars directly. They can detect carbon dioxide (CO2), carbon monoxide (CO), nitrogen oxides (NOx), hydrocarbons (HC), and particulate matter (PM).

On-Board Diagnostics (OBD) Systems: Many modern vehicles come equipped with OBD systems that monitor emissions-related components. OBD scanners can be used to access data from these systems, providing information about emissions and detecting potential issues.

Portable Emission Measurement Systems (PEMS): These are portable devices used to measure emissions during real-world driving conditions. PEMS can be attached to a vehicle to collect data on emissions while it's being driven on roads.

Gas Sensors: Gas sensors capable of detecting specific pollutants like CO2, CO, NOx, and hydrocarbons can be used in conjunction with data loggers or microcontrollers to monitor emissions.

Lidar and Optical Sensors: Advanced sensors like Lidar (Light Detection and Ranging) or optical sensors can detect and measure particulate matter emissions from vehicles. Data Loggers and Microcontrollers: These components are often used to collect, process, and store data from various sensors. They can be used in emission detection systems to manage and analyze the data obtained from different sensors.

Telematics Devices: These devices can transmit real-time vehicle data, including emissions-related information, to remote servers or systems for monitoring and analysis.

Vehicle Emission Testing Equipment: This includes dynamometers and testing chambers used in controlled environments to measure emissions under specific conditions, allowing for accurate testing and comparison.

The actual work starts after the recording of the readings from the sensors, where Carbon emission prediction algorithms play a crucial role in understanding and forecasting the impact of human activities on the environment. These algorithms use various techniques and data sources to estimate future carbon emissions.

B. Common Approches

"Fig. 3", shows the Carbon emission prediction algorithms

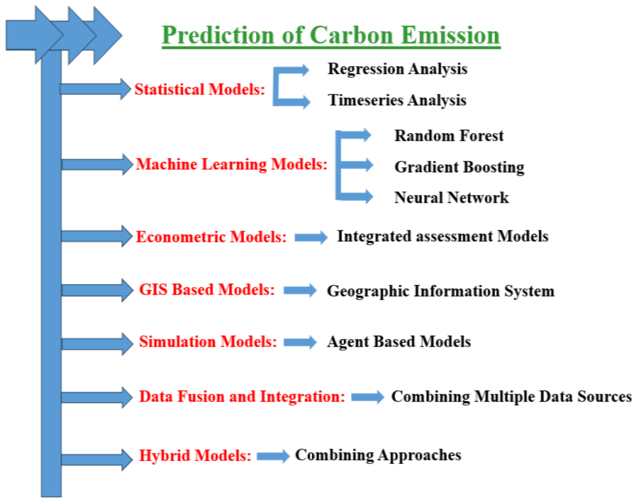

Fig. 2. Carbon emission prediction algorithms

1. Statistical Models:

a. Regression Analysis: Linear regression or multiple regression models can be employed to establish relationships between carbon emissions and various influencing factors such as population, industrial output, and energy consumption.

b. Time Series Analysis: Time series models, like ARIMA (AutoRegressive Integrated Moving Average), can be used to analyze historical carbon emission data and identify patterns or trends.

2. Machine Learning Models:

a. Random Forest: Random Forest algorithms can capture complex relationships between input variables and carbon emissions. They are robust and can handle non-linear patterns in the data [13,14].

b. Gradient Boosting: Algorithms like XGBoost or LightGBM are effective for predicting carbon emissions. They build an ensemble of weak learners to improve prediction accuracy.

c. Neural Networks: Deep learning models, such as artificial neural networks, can learn intricate patterns in large datasets. Time series data can be handled by Long Short-Term Memory (LSTM) networks or Recurrent Neural Networks (RNNs) [15,16].

3. Econometric Models:

a. Integrated Assessment Models (IAMs): IAMs combine economic and environmental components to simulate the interactions between economic activities and carbon emissions. These models are often used for long-term policy analysis.

4. GIS-Based Models:

a. Geographic Information System (GIS): Combining carbon emission data with spatial information using GIS can provide insights into localized emissions. GIS-based models can help in predicting emissions at specific geographical locations.

5. Simulation Models:

a. Agent-Based Models (ABMs): ABMs simulate the behavior of individual entities (agents) within a system. They can be used to model the decisions and interactions of individuals, organizations, or governments that influence carbon emissions.

6. Data Fusion and Integration:

a. Combining Multiple Data Sources: Integrating diverse datasets, including satellite imagery, climate data, and socioeconomic indicators, can enhance the accuracy of carbon emission predictions.

7. Hybrid Models:

a. Combining Approaches: Hybrid models that combine statistical, machine learning, and simulation techniques can leverage the strengths of each approach for more accurate predictions.

3. Methodology Used

While designing a system for vehicular carbon emission detection, it's crucial to select appropriate sensors and hardware components based on the specific emissions being targeted, environmental conditions, data accuracy requirements, and intended application. Implemented IoT device contains MQ9 Sensor, NEO6M GPS with Antenna, OLED Screen and ESP32 DEV Board. PM sensor measures PM 2.5 and PM 10 values. Here, in an integrated system PM 2.5 sensor is used to measure pollution as per Indian environment. It's a temperature and humidity sensor, formaldehyde, PM 2.5, and DFRobot air quality monitor. It has four pins Vcc (+5 Volts), Ground (Gnd) its negative, Rx (Receiver), Tx (Transmitter).

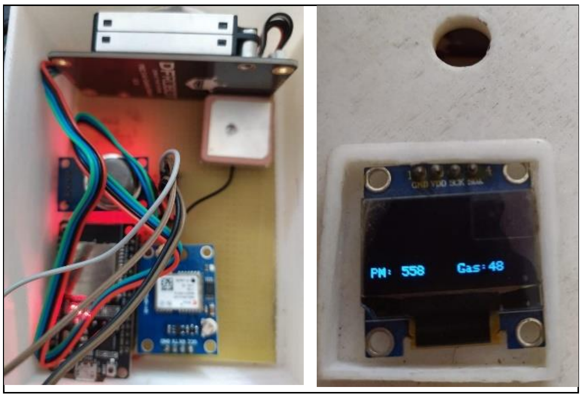

Fig. 3. IoT Device Implementation

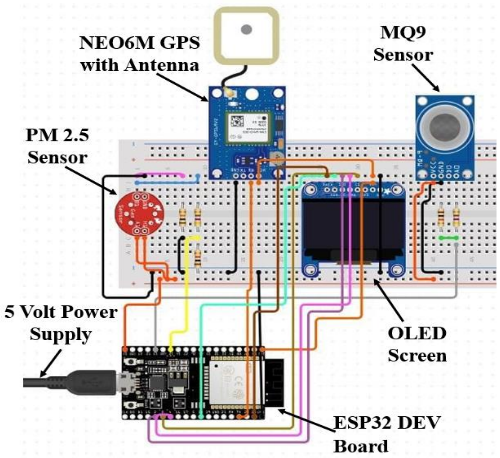

Fig. 4. Circuit representation of IoT Device

GPS with Antenna is used in the device. The NEO-6M GPS Module used for GPS tracking, positioning information. It is used with cars and other mobile applications. It's GPS processing unit has four pins Vcc (+5 Volts), Ground (Gnd) its negative, Rx (Receiver), Tx (Transmitter). Rx receives data from antenna and after processing transmitter transmits the data in the form of coordinates latitude and longitude. Transfers data is in the form of packets to ESP32. Based on the ESP WROOM32 WIFI + BLE (Bluetooth) Module is the development board. The ESP-WROOM-32 module powers this small, minimalist system development board, which fits neatly into a solderless breadboard.. Here, ESP32 works like a computer to process the received data packets and displayed the data in the human readable format. Gas and Dust Sensor also used in the device.

MQ-9 Carbon Monoxide, Methane and LPG Gas Sensor Module is used in the device to measure the gases carbon monoxide and carbon di oxide (CO_2). Good sensitivity to CO/Combustible gases, high sensitivity to Methane and Propane gases. It has long life, low-cost and simple drive circuit which has Input voltage DC 5±0.2V. It contains 4 pins as well out of which two pins are common Vcc and Grd. Analog and digital pins are also present out of which this device uses digital pin. MQ-9 sensors digital pin sends data to ESP-32 in the form of packet. Received data from MQ9 Sensor, NEO6M and PM 2.5 Sensor processed by ESP-32 and displayed it through OLED Screen.

Using the micro-controller ESP-32, a 0.96-inch OLED module is used to immediately present text and graphical data. Numerous chips are supported, including the STIM 32, 51 MCU, Raspberry Pi, Arduino UNO, and Mega. It also contains 4 pins and these pins has connection with ESP-32. It displays the processed data of ESP-32 in the readable format.

"Fig. 3", shows the real image of the device. All the connections of the breadboard packed in the box to made the device and the hole shown on box is used to put the connection tube through tail pipe of the vehicle to measure the emission values. The OLED screen displays all sensor values on the screen. "Fig. 4", shows Circuit diagram of the implemented device with the internal circuit connections.

The device that implemented is connected with the Mobile application using Wi-Fi through ESP-32. Anywhere in the World you can access the data of this device using the web application or through mobile application. The data generated through the device transferred through the cloud. The cloud that is used in this system is Blynk. The received data through

the cloud is shown in the mobile application through gauge and charts. The values displayed on the OLED screen are the same values displayed in the mobile or web application. By using these values data get collected.

C. Algorithm for the prediction of the carbon emission is as follows:

The sensor sends the data to the server. By using Python script, the data from the server is extracted. the extracted data is then passed through the Adaptive Boosting ML algorithm (ABML).

1. For a dataset with N number of samples, we initialize the weight of each data point with $w_i = \frac{1}{N}$.

2. For m=1 to M :

a. Sample the dataset using the weights $w_i^{(m)}$ to obtain training samples x_i.

b. Fit a classifier K_m using all the training samples x_i ground truth value of the target variable, and w_i^m is the weight of the sample i at iteration m.

c. Compute $\alpha_m = \frac{1}{2} \ln \frac{1-\epsilon}{\epsilon}$.

d. Update all the weights $w_i^{(m+1)} = w_i^{(m)} e^{-\alpha_m y K_m(x)}$.

3. New predictions computed by

$K(x) = \text{sign}\ [\sum_{m=1}^{M} \alpha_m K_m(x)]$.

In this, we have studied various research papers and a brief explanation about the research paper was explained with the research gap mentioned in the year. Here we have studied the various technology used to calculate carbon emission in an environment so that various precautionary measures can be applied and implemented using new technologies and mobile applications to protect the living environment [20,21].

The 70% data is used for the training ABML model. Then the results are calculated on remaining 30% data. The results of the proposed ABML algorithm along with another existing algorithms are presented in next session.

4. Results And Discussion

The hardware device get connected to the server and via server the readings get reflected to the mobile application as shown in "Fig. 5,6 & 7".

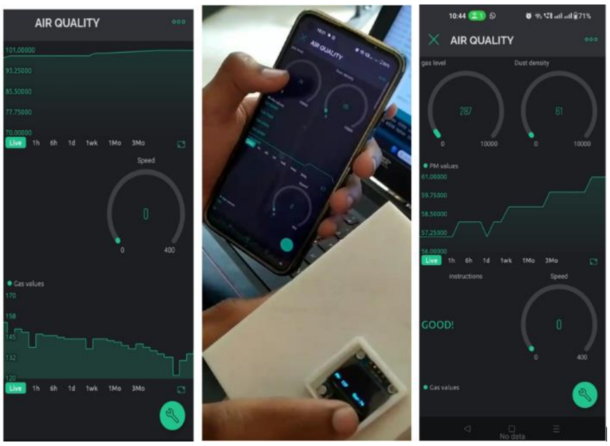

Fig. 5. Connection of Device with Mobile application

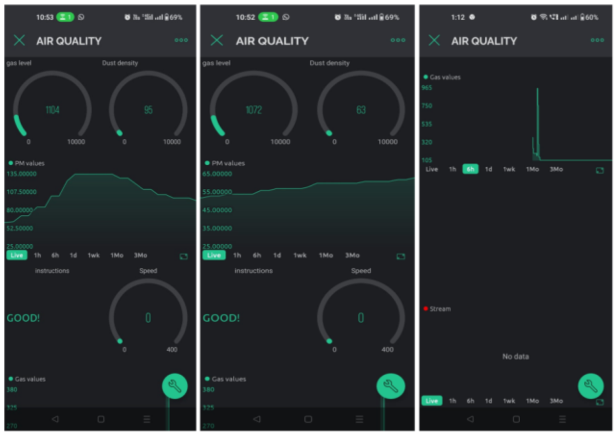

Fig. 6. Values captured through mobile application

Fig. 7. Values captured through web application

The dashboard and the notification window are presented in "Fig. 5,6 & 7". It shows the sensor readings along with the instructions and speed in the well-designed graphical representation. The forecasting of the carbon emission is done by using Python scripts. For prediction purposes, we have tried many algorithms and then finalized one based on mean squared value (MSE). The comparative analysis is presented in table 1.

TABLE I. VALUE OF MSE FOR DIFFERENT ML ALGORITHMS

Algorithm	MSE
ABML	0.083
Support Vector Machine (SVM)	0.128
Decision Making (DM)	0.328
Logistic Regression	2.414
Random Forest	3.414
Linear Regression	2.591
K-nearest neighbours	1.942
Ridge Regression	2.95
Gradient Boosting	0.179

For better visual representation of the table 1 is graphically presented as "Fig. 8". The conclusion from the figure 8 can be easily made as the value of MSE is very less as compared to all the other algorithms.

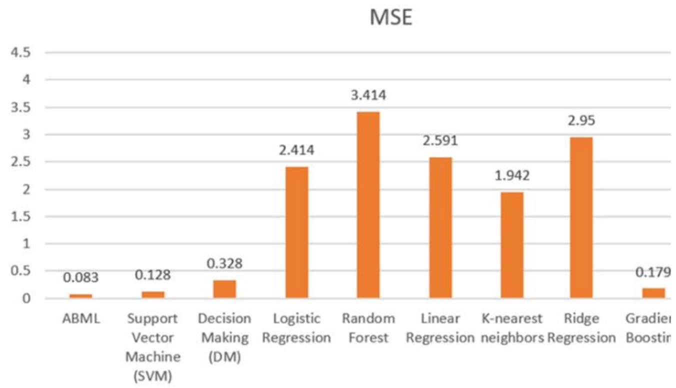

Fig. 8. The value of MSE for different ML algorithms

The time complexity [18] of the ABML is calculated on different hardware platforms and is presented in table 2.

TABLE II. THE TIME COMPLEXITY OF THE ABML ALGORITHM ON DIFFERENT HARDWARE PLATFORMS

Hardware Platform	**Time required to get result (in seconds)**
CPU, i3 processor, 8GB RAM	4.395
CPU, i5 processor, 8GB RAM	4.163
CPU, I7 processor, 8GB RAM	3.124
GPU, Nvidia K80	0.962

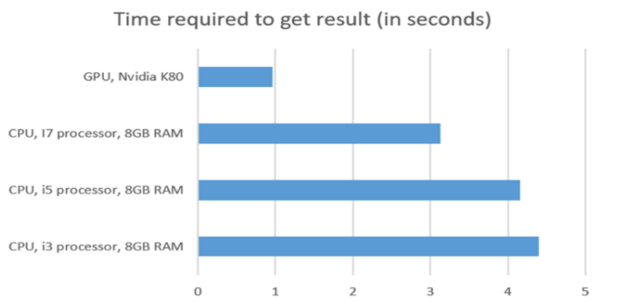

Fig. 9. Time complexity of the ABML on different hardware platforms

"Fig. 9" shows the Time complexity of the ABML on different hardware platforms in terms of seconds.

It comes to know that, the time complexity of ABML is highly depends on the hardware platform which is used. To get the lowest time complexity it is preferred to use the GPU.

5. Conclusion

The paper proposes the hardware model for the getting the carbon emission from the vehicle along with the forecasting of it. The paper gives complete idea about the techniques used for the forecasting purposes. The paper gives idea about how ABML is the best choice for the prediction of the carbon emission. The MSE of the ABML while predicting the values is 0.083. The proposed ABML gives lowest MSE value when we compared it with another nine ML algorithms. The time complexity of the ABML is also calculated. The result of the prediction definitely helps to reduce the carbon emission.

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